LA-UR-19-29870
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Title: Fault systems monitoring using machine learning

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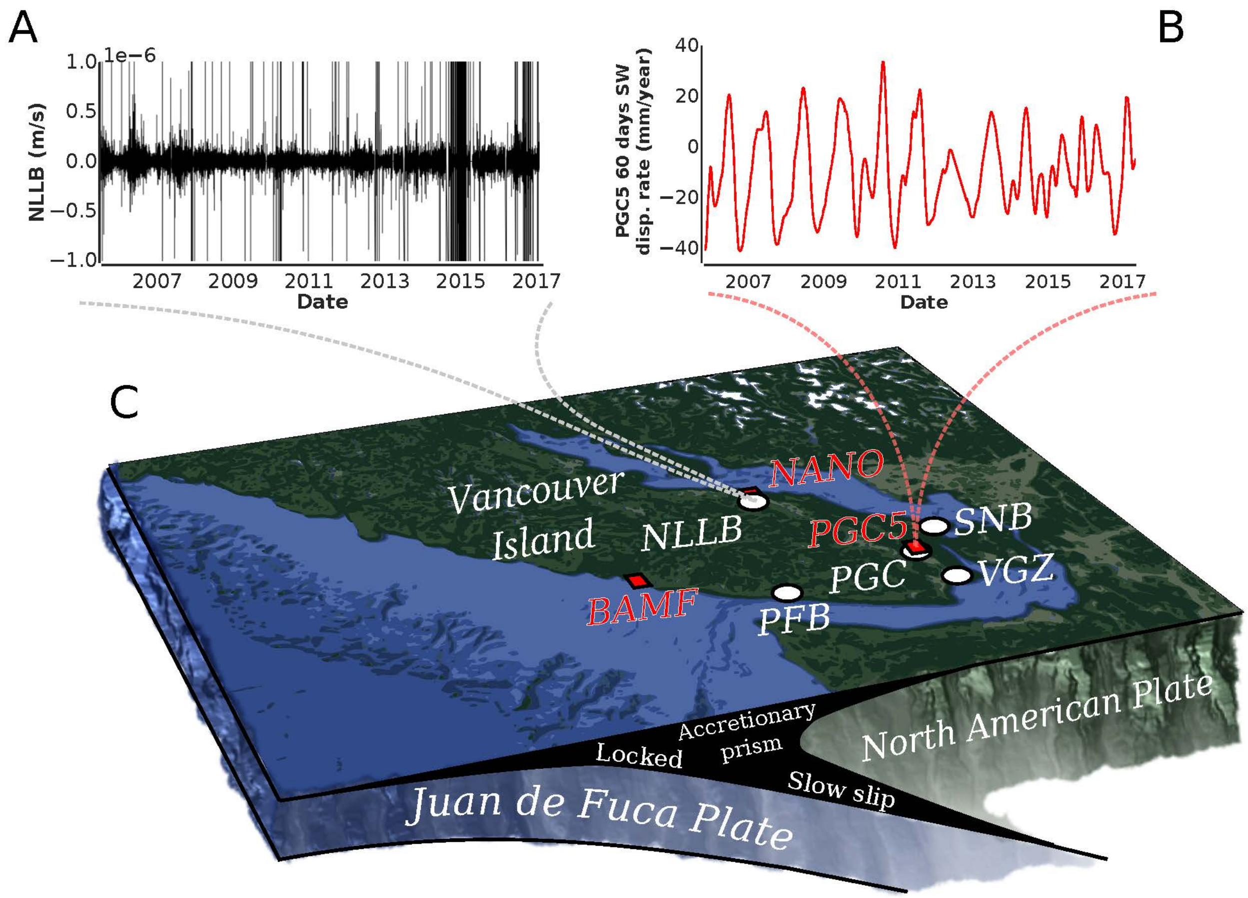
Intended for: Web

Issued: 2019-09-30

Title of Technology Fault systems monitoring using machine learning

Subtitle Continuous seismic data analysis using Artificial Intelligence and machine learning



Summary

Traditional seismology methods are designed to build catalogs of seismic events that are obviously different from the remaining seismic data, even to the naked eye, and discard more than 99% of the data. Los Alamos National Lab researchers developed machine learning methods to examine massive amounts of raw seismic data. The scientists found that the continuous data discarded by cataloging methods are informative of the physical state of faults in theoretical models, in laboratory experiments, and in the field. This information may enable the detection of predictive markers of seismic events and the provide insights into the underlying physics to support earthquake hazard assessment.

Market

Earthquakes in the U.S. cause an average of more than $6 B direct damage annually. Few homes are insured due to the unpredictability of earthquakes. Our laboratory scale research shows that earthquakes should be predictable in some cases, and our first field applications of machine learning to Cascadia slow earthquakes confirms the opportunity to drastically improve earthquake forecasting, with a dynamic evaluation of risk.

The surge in seismicity related to wastewater disposal associated with shale gas and oil extraction (*e.g.*, approximately 900 fold increase in Oklahoma) has led to disruptions and regulation associated with induced seismicity. Our machine learning methods can also identify the evolution of the physical state of fault systems induced to failure by fluid injection, with the potential to provide real time monitoring for extraction operators and regulators.

Benefit Summary

Traditional seismology methods that catalog earthquakes do not reliably capture precursory activity from faults. Our method of mapping continuous seismic data to the state of faults using Artificial Intelligence (AI) and machine learning enables the continuous monitoring of faults and their associated seismic risk. These benefits include:

Benefit List

- Use full continuous seismic datasets. Field applications to Cascadia slow earthquakes and induced earthquakes in France have revealed a significant fraction (20 to 50%) of the data to carry useful information, while catalog methods only retain 1% of this information.
- Are fully automatic, whereas most cataloging methods involve a human picking earthquake waveforms at some point.
- Provide a quantifiable relation between features of continuous seismic data and physical quantities of interest (*e.g.*, fault friction, fault displacement rate, permeability of fault system), whereas catalogs need further interpretation to be related to physical quantities.
- Techniques may be extendable to other catastrophic rock failure scenarios such as landslides

Why are we Building

Conventional methods attempting earthquake prediction use processed seismic data (e.g., earthquake magnitude, locations, and times) – called earthquake catalogs. These methods examine only a small portion of data, leaving much potentially useful data unexplored.

Our goal is to identify small yet informative signals from discarded geophysical data, seismic data in particular. These previously undetected signals provide meaningful tremor statistics that are frequently a fingerprint of the displacement rate of the fault. This approach has enabled us to demonstrate that at least in some instances earthquakes are in fact predictable, and that fault systems emit signals informative of their physical state in real time.

What's behind our Technology?
The technology we have developed is entirely based on supervised machine learning techniques, a branch of AI where models relating inputs to outputs are automatically explored. This enables us to

detect minute and complex patterns in seismic data that are related to the physical state of faults or fault systems.

In comparison other seismology methods can be seen as unsupervised methods, where there is no output, and instead the inputs are separated based on how different they are (earthquakes versus noise).

Our Competitive Advantages

Our technology is fully automatic and leverages the available seismic data in its entirety, compared to standard seismology methods that only use a fraction of the data (less than 1%) and require human intervention.

Our machine learning based methods give access to physical properties of fault systems in real time, such as fault friction, deformation, and permeability, something seismology methods do not give access to. Our methods determine quantifiable relationships, whereas catalogs require further interpretation to be related to physical quantities.

Our Technology Status

Our technology has been demonstrated to work in a field environment (Cascadia slow earthquakes and induced earthquakes in France). The path for the technology to be commercialized is to demonstrate a live feed of seismic data to our models, in real time and on dedicated servers. The product would be a live map of fault properties that are monitored: dynamic evaluation of seismic hazard increase or decrease, deformation on faults, permeability of fault systems. Such technology development could be pursued through a CRADA or other partnering agreement.

Publications and IP

Rouet-Leduc, B., Hulbert, C., Lubbers, N., Barros, K., Humphreys, C. J., and Johnson, P. A. (2017). Machine learning predicts laboratory earthquakes. Geophysical Research Letters, 44, 9276–9282. https://doi.org/10.1002/2017GL074677

Rouet-Leduc, B., Hulbert, C., Bolton, D. C., Ren, C. X., Riviere, J., Marone, C., Guyer, R. and Johnson, P. A. (2018). Estimating fault friction from seismic signals in the laboratory. Geophysical Research Letters, 45, 1321–1329. https://doi.org/10.1002/2017GL076708

Rouet-Leduc, B., Hulbert, C., and Johnson, P. A. (2018). Continuous chatter of the Cascadia subduction zone revealed by machine learning, Nature Geoscience 12, 75-79. doi.org/10.1038/s41561-018-0274-6 https://doi.org/10.1038/s41561-018-0274-6

Hulbert, C., Rouet-Leduc, B., Johnson, P. A., Ren, C. X., Rivière, J., Bolton, D. C., and Marone, C. (2019). Similarity of fast and slow earthquakes illuminated by machine learning. Nature Geoscience, 12, 69-74. https://doi.org/10.1038/s41561-018-0272-8

Two patent applications are associated with this technology.

Additional Media
Video from the LANL communications office:
https://www.youtube.com/watch?v=mPaZmrpy7ng

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